The Long-term Decline of the U.S. Job Ladder

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Abstract

We develop a methodology to consistently estimate *employer-to-employer* (EE) mobility toward higher paying jobs based on publicly available microdata from the *Current Population Survey*, and use it to document three facts on U.S. mobility over the past half century. First, EE mobility toward higher paying jobs fell in half between 1979 and 2023. Second, the fall in EE mobility toward higher paying jobs was associated with over a one percentage point decline in annual wage growth. Third, the decline in EE mobility and its associated wage growth was particularly pronounced for women, minorities, those with less than a college degree, and recent cohorts. We argue that the decline in EE mobility is unlikely to be the result of workers being better matched with their current jobs or the labor market being worse at matching workers and firms. Instead we conclude based on variation across U.S. local labor markets that greater labor market concentration may have reduced workers' opportunities to switch employers.

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1 Introduction

Shopping for jobs is an integral part of workers' careers. Young workers enter the labor market poorly matched, and gradually relocate across firms to find better matches. Topel and Ward (1992) find that this process of *employer-to-employer* (EE) mobility accounts for a third of workers' wage growth during the first 10 years of their careers. More recently, macroeconomists have stressed that such mobility also plays a critical role for aggregate economic performance, by reallocating workers from less to more productive firms (Lentz and Mortensen, 2012; Moscarini and Postel-Vinay, 2017; Bilal et al., 2022; Elsby and Gottfries, 2022). Yet, despite its importance for both micro and macroeconomic outcomes, little is known about long-run trends in EE mobility in the U.S.

This paper proposes a methodology to consistently estimate EE mobility toward higher paying jobs over the past half century in the U.S., overcoming data limitations that so far have prevented a long-run historical analysis (Molloy et al., 2016). Applied to publicly available micro data from the *Current Population Survey* (CPS), we document three new facts on trends in U.S. EE mobility. First, such mobility fell in half between 1979 and 2023. Second, its decline contributed to over one percentage point weaker annual wage growth today relative to the 1980s. Third, the fall was particularly pronounced for women, minorities, those with less than a college degree, and recent cohorts. We proceed to analyze factors behind the decline in EE mobility, finding that it is unlikely to be the result of workers being better matched with their current employers or the labor market being worse at matching workers and firms. Instead, we argue based on variation across U.S. local labor markets that greater labor market concentration may have reduced workers' opportunities to switch employers (Bagga, 2023; Jarosch, Nimczik and Sorkin, 2024).

Our methodology is based on a prototypical job ladder model in the spirit of Burdett and Mortensen (1998). In the baseline version, the only source of wage growth is EE mobility. In each period, non-employed and employed workers receive job offers with some exogenous and potentially different probability. A job offer is a draw of a wage from an exogenous wage offer distribution, which may also vary by employment status (Faberman et al., 2022). If the worker accepts the job, she supplies a unit of labor at the specified wage until either she finds a new job offering a higher wage or her job exogenously terminates and she becomes non-employed.

The model predicts that the number of workers earning at most a wage w in period $t+1$ depends on the number of workers paid at most w in period t, the number of these workers who separated to non-employment between periods t and $t+1$, the fraction who made an EE transition to a job paying more than w between t and $t+1$, and the number of non-employed workers in period t who found a job paying at most w in period $t+1$. Knowledge of all the other objects in this relationship allows us to recover the EE transition probability. The logic is best illustrated by an example. Consider an economy in which 10 workers earn a wage below w in period t. Suppose that between periods t and $t+1$, one of these workers separates to non-employment, while two workers are hired from non-employment into jobs paying less than w. In period $t+1$, we again record 10 workers earning less than w. Then the fraction $x_t(w)$ of workers employed at a wage less than w in period t that made an EE transition to jobs paying more than w in period $t+1$ solves

$$\underbrace{10}_{\text{earning} \leq w \text{ at } t} - \underbrace{1}_{\text{employment outflows}} + \underbrace{2}_{\text{employment inflows}} - \underbrace{10x_t(w)}_{\text{EE moves from} \leq w \text{ to} > w} = \underbrace{10}_{\text{earning} \leq w \text{ at } t+1}$$

In this example $x_t(w) = 10\%$. That is, 10 percent of workers earning less than w in period t made an EE transition to a job paying more than w in period $t+1$. Knowledge of this share as well as the share of all workers who are paid w for each wage w in period t allows us to compute the overall EE transition probability to higher paying jobs in period t.

To compute the inputs required to estimate EE mobility, we use data from the basic monthly survey and the *Outgoing Rotation Group* (ORG) of the CPS. Specifically, we record an individual's employment status in each month during a four month period, her hourly wage in the last of these four months, and demographic characteristics. Since our model assumes that all wage growth is due to EE mobility, we residualize wages on a rich set of demographic controls that account for wage growth with experience as well as for the impact of aggregate trends. Subsequently, we measure the share of workers earning less than (residual) wage w in months t and $t+1$, the share of hires from non-employment who earn a wage below w in month $t+1$, and the share of employed workers in month t who are non-employed in period $t+1$. Through the lens of our theory, these objects are sufficient to recover the EE transition probability in month t.

Our structural approach to estimating EE mobility features three advantages over computing EE mobility as the fraction of workers at different employers in two consecutive months—what we refer to as *raw EE mobility*. First, it allows us to document worker flows from 1979 to 1994,[1] a period of significant economic change in the U.S for which the raw series is not available. Second, it overcomes data challenges such as the bias introduced by changes to the CPS over time (Fujita, Moscarini and Postel-Vinay, Forthcoming) as well as *seam bias*, the tendency to report changes occurring between interview blocks rather than within them (Polivka and Rothgeb, 1993). Third, our methodology identifies only those EE transitions that move a worker toward higher paying jobs, whereas a substantial share of EE moves in raw data are toward lower paying jobs (Tjaden and Wellschmied, 2014; Sorkin, 2018). For aggregate economic performance, the former may be more relevant (Moscarini and Postel-Vinay, 2017; Bilal et al., 2022; Elsby and Gottfries, 2022).

On the other hand, there are at least two important concerns with our methodology. First, we assume that after taking out the effect of observable characteristics such as experience, residual wage growth is driven by EE mobility. Although this assumption is consistent with recent work highlighting the central role of EE mobility for wage dynamics (Karahan et al., 2017; Moscarini and Postel-Vinay, 2017; Ozkan, Song and Karahan, 2023; Tanaka, Warren and Wiczer, 2023), we provide an extension that incorporates on-the-job residual wage growth with job tenure. Second,

[1] Although we have not yet attempted to do so, it should be possible to extend our analysis back to 1976.

we abstract from unobserved heterogeneity, which a recent literature stresses as an important determinant of worker flows (Hall and Kudlyak, 2019; Morchio, 2020; Gregory, Menzio and Wiczer, 2021; Ahn, Hobijn and Şahin, 2023).[2] To assess its importance, we merge data from two ORG surveys, and residualize a worker's current residual wage also off her previous residual wage.

We establish three new facts on trends in U.S. EE mobility over the past 45 years. First, EE mobility toward higher paying jobs declined sharply between 1979 and 2023. The monthly EE transition probability fell from 1.5 percent in the 1980s to less than one percent today, with only a short-lived reversal during the Pandemic. Allowing for time-varying on-the-job growth in residual wages with tenure has only a minor effect on our estimates, due to the fact that such wage growth is uniformly small (see Molloy et al., 2016, for similar evidence). Furthermore, although hires from non-employment earned 5–15 percent lower residual wages in their previous job, such negative selection on unobservables does not appear to have changed over time. Consequently, controlling for it does not affect our finding of a large decline in EE mobility over the past decades.

Second, the fall in EE mobility was associated with a sizeable decline in wage growth, as workers made fewer transitions toward higher paying jobs. Our estimates imply that EE mobility toward higher paying jobs contributed over three percentage points to annual wage growth in the 1980s. As mobility declined, so did the wage gains associated with it. In fact, despite an increase in the average wage gain conditional on an EE transition, the declining frequency of EE transitions contributed to over one percentage point weaker annual wage growth today.

Third, although the decline in EE mobility and its associated wage growth was pervasive across demographic groups, it was particularly pronounced for women, black workers, those with less than a college degree, and young workers. The latter in consistent with the evidence provided by Bosler and Petrosky-Nadeau (2016) using the SIPP between 1996 and 2012. Furthermore, under the assumption that mobility is flat with age later in careers—as predicted by prototypical job ladder models—we can decompose the change in EE mobility over time into a time, age and cohort effect (Heckman, Lochner and Taber, 1998; Lagakos et al., 2018). We find an important role for cohort effects in accounting for the aggregate decline in EE mobility. That is, recent cohorts are less mobile than older generations, controlling for factors that affect mobility of all cohorts.

Having established these facts regarding trends in EE mobility and its associated wage growth over the past half century in the U.S., we proceed to analyze potential factors behind them. One possibility is that workers today are better matched in the labor market, so that they are less likely to accept an outside job offer (Mercan, 2017; Pries and Rogerson, 2022). Two observations lead us to downplay the quantitative relevance of this explanation. First, we find that EE switchers on average make a larger wage gain today than 40 years ago. At face value, the greater return to mobility appears at odds with the notion that workers are better matched today. Molloy et al. (2016) draw a similar conclusion to ours based on the lack of a long-run trend in starting wages. Second, we estimate that workers are no less likely to reject an outside offer today. In fact, the

[2] Clark and Summers (1979) originally stressed the importance of unobserved heterogeneity for labor market flows.

acceptance probability modestly rose over time. Hence, the decline in EE mobility is entirely accounted for by a lower probability that an employed worker receives an outside job offer.

The decline in the job finding probability of the employed could, for instance, be the result of changes in the efficiency at which the labor market matches workers and firms. Alternatively, firms might advertise fewer job openings today. Benchmark equilibrium theories of the labor market predict that such forces would *proportionately* reduce the job finding probability of the employed and non-employed. In contrast, we find that the job finding probability of the employed declined by much more than that of the non-employed, suggesting that the decline in EE mobility was not primarily the result of changes in matching efficiency or firms' recruitment efforts.

Our results instead point to factors that particularly impacted the job finding prospects of the employed. Two hypotheses consistent with this pattern are the increased use of non-compete agreements that may discourage on-the-job search (Gottfries and Jarosch, 2023) or greater labor market concentration which limits workers' outside options (Bagga, 2023; Jarosch, Nimczik and Sorkin, 2024). In line with the latter view, we conclude by documenting that the job finding probability of the employed declined disproportionately in regions that saw larger increases in labor market concentration. Specifically, we replicate our analysis for each of the nine U.S. Census divisions, and merge the resulting data set with measures of the number of firms per worker from the U.S. Census *Business Dynamic Statistics* (BDS). We project the job finding probability of the employed at the division-5-year period level on the number of firms per worker, division and period fixed effects. Our results reveal a strong negative correlation between labor market concentration and the job finding probability of the employed. Indeed, the point estimate would imply that the increase in labor market concentration observed at the national level between 1979 and today accounts for more than 40 percent of the fall in EE mobility over this period.

Literature. This paper relates to the large literature studying declining "economic dynamism". Davis and Haltiwanger (2014) and Decker et al. (2016) document a decline in job reallocation in the U.S. since the 1980s—a measure of *net* worker reallocation. While our finding of a decline in EE mobility mirrors their result, we argue that the former does not follow mechanically from the latter. This is because although a worker must switch employer whenever a job switches firm, the opposite is not true. Instead, a firm can hire a new worker to replace a worker who leaves (Faberman and Nagypál, 2011; Mercan and Schoefer, 2020; Bachmann et al., 2021; Elsby et al., 2023). Indeed, we find that worker reallocation is about four times as large as job reallocation. Furthermore, most of the decline in worker reallocation is not accounted for by the fall in job reallocation, but by a decrease in replacement hiring (Hyatt and Spletzer, 2013). Nevertheless, Davis, Faberman and Haltiwanger (2012) show that job reallocation is correlated with *excess worker reallocation*—the component of worker reallocation that is not mechanically accounted for by job reallocation. Based on their finding, one may expect the decline in job reallocation to be reflected also in a fall in excess worker reallocation. Pries and Rogerson (2005) show, however, that net flows are similar across countries, but gross flows differ substantially, suggesting that job reallocation and excess worker reallocation are not perfectly correlated. In any case, even if the correlation between net and gross flows were perfect, worker reallocation could take the form of EE mobility or reallocation through non-employment. Since these forms of reallocation have vastly different implications for workers, it is important to dissect the nature of the changes in worker flows.

Recently, EE flows have received much attention in the macro-labor literature, given their importance for overall worker flows (Fallick and Fleischman, 2004; Krause and Lubik, 2006; Nagypal, 2008).[3] Hyatt and Spletzer (2013), Hyatt (2015) and Haltiwanger et al. (2018) study trends in EE mobility using matched employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) program starting in 1998. Fujita, Moscarini and Postel-Vinay (Forthcoming) show that changes in non-response rates bias the raw measure in the CPS toward an excessively large decline in EE mobility in recent years. Molloy et al. (2016) provide a comprehensive analysis of trends in U.S. labor market dynamics over the past 40 years, proxying for the EE transition probability using the number of employers a respondent had in the previous calendar year following Blanchard and Diamond (1990) (Shimer, 2005, and Diamond and Şahin, 2016, use the same proxy to study EE mobility over the business cycle). As these papers acknowledge, this is an imperfect proxy because it risks misclassifying, for instance, employment-unemployment-employment transitions as EE transitions and it records at most two EE transitions in the previous calendar year. Hyatt and Spletzer (2016, 2017) and Molloy, Smith and Wozniak (2024) infer changes in worker mobility based on the tenure distribution.

Our motivation is shared by Shimer (2012), who applies a parsimonious model of labor market flows to unemployment duration data to infer the separation probability to and job finding probability from unemployment starting in 1948. Jolivet, Postel-Vinay and Robin (2006) discipline a partial equilibrium search model using cross-country micro data on wages and labor market flows, finding that such data allow an estimate of on-the-job search.

Finally, a rapidly growing literature studies the impact of labor market power on wages and employment (Macaluso, Hershbein and Yeh, 2019; Azar et al., 2020; Prager and Schmitt, 2021; Azar, Marinescu and Steinbaum, 2022; Berger, Herkenhoff and Mongey, 2022; Benmelech, Bergman and Kim, 2022; Handwerker and Dey, 2022; Rinz, 2022; Caldwell and Danieli, 2024). Most closely related, Bagga (2023) finds a positive correlation between EE mobility and the ratio of firms to workers across U.S. local labor markets. Due to data limitations, however, she is restricted to analyze the cross-sectional relationship, as opposed to the within-region patterns that we study. While both papers lack a credible identification strategy to obtain a causal estimate, within-region variation arguably reduces concerns about third factors driving the correlation. Berger et al. (2023) correlate measures of market concentration with worker flows both across and within local labor

[3] This builds on an earlier literature that aimed to understand unemployment as an equilibrium phenomenon (Diamond, 1982; Mortensen and Pissarides, 1994), and which later incorporated an active labor supply margin to also match flows in and out of non-participation (Elsby, Hobijn and Şahin, 2015; Krusell et al., 2017). Early work that incorporates on-the-job search include Burdett (1978), Pissarides (1994) and Burdett and Mortensen (1998).

markets in Norway between 2006 and 2018. Consistent with our result, they find a negative relationship between the two. Our result complements their finding by offering a longer time series and by providing evidence from the U.S., whose institutional setting may differ in important dimensions from Norway's.

We start by outlining our partial equilibrium job ladder model in section 2. Section 3 discusses the data and our estimation procedure. In section, 4 we present long-term trends in EE mobility and its associated wage growth in the aggregate and within sub-populations. Section 5 discusses the potential causes for the decline in EE mobility. Finally, section 6 concludes.

2 Methodology

This section outlines a parsimonious partial equilibrium model of worker dynamics in the spirit of Burdett and Mortensen (1998) set in discrete time. The job finding probabilities, the separation probability, and the wage offer distribution are all taken as exogenous. While stylized, an extensive literature finds that this framework is remarkably successful at matching empirical labor market dynamics (Jolivet, Postel-Vinay and Robin, 2006).

2.1 Environment

Time $t \geq 0$ is discrete and infinite. A unit mass of ex-ante identical, infinitely lived workers move across jobs as well as in and out of employment. Let e_t denote the employment rate at time t.

Non-employed workers receive job offers with exogenous probability $\lambda_t^n \in [0,1]$. A job offer is a draw of a (log) wage w from an exogenous *wage offer distribution* of the non-employed. Let $f_{t+1}^n(w)$ denote its probability density function (pdf) and $F_{t+1}^n(w)$ its cumulative distribution function (cdf), distributed over support $w \in (-\infty, \infty)$. We assume that non-employed workers accept any job offer they receive.[4] The wage remains fixed for the duration of the match.

With exogenous probability $\lambda_t^e \in [0,1]$, an employed worker receives an outside offer from a wage offer distribution of the employed, whose pdf (cdf) we denote $f_{t+1}^e(w)$ ($F_{t+1}^e(w)$). Since workers choose whether to accept an offer, they only switch to jobs that offer higher wages.

Finally, employed workers separate to non-employment with exogenous probability $\delta_t \in [0,1]$. We require that these probabilities satisfy $\delta_t + \lambda_t^e \leq 1$.

[4]This assumption can be motivated by the fact that no firm would find it optimal to advertise a job paying less than the reservation wage common to all non-employed workers.

2.2 Labor market flows

The number of workers earning wage w at time t, $g_t(w)e_t$, evolves according to

$$g_{t+1}(w)\,e_{t+1} = g_t(w)e_t - \underbrace{\delta_t g_t(w)e_t}_{\text{separations to nonemp.}} - \underbrace{\lambda_t^e\left(1-F_{t+1}^e(w)\right)g_t(w)e_t}_{\text{EE separations}} + \underbrace{\lambda_t^n f_{t+1}^n(w)(1-e_t)}_{\text{hires from nonemp.}} + \underbrace{\lambda_t^e f_{t+1}^e(w)G_t(w)e_t}_{\text{EE hires}} \tag{1}$$

Integrating (1) from $-\infty$ to w, applying integration by parts, gives[5]

$$G_{t+1}(w)\,e_{t+1} = \left(1-\delta_t-\lambda_t^e(1-F_{t+1}^e(w))\right)G_t(w)e_t + \lambda_t^n F_{t+1}^n(w)(1-e_t)$$

which we can rearrange as

$$\underbrace{\lambda_t^e\left(1-F_{t+1}^e(w)\right)}_{sep_t^e(w)\equiv\text{poaching separation probability}} = 1 - \frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t} + \lambda_t^n\frac{F_{t+1}^n(w)}{G_t(w)}\frac{1-e_t}{e_t} - \delta_t \tag{2}$$

We discuss below how to measure $G_t(w)$, $G_{t+1}(w)$, $F_{t+1}^n(w)$, e_t, e_{t+1}, λ_t^n and δ_t in the CPS. Provided these objects, we can estimate the *poaching separation probability* at each wage w based on (2). The EE transition probability is then the average poaching separation rate

$$EE_t = \lambda_t^e\int_{-\infty}^{\infty}\left(1-F_{t+1}^e(w)\right)dG_t(w) = \int_{-\infty}^{\infty} sep_t^e(w)dG_t(w) \tag{3}$$

2.3 Wage growth due to EE mobility

Wage growth due to EE mobility is the fraction of workers who receive a job offer times the average wage gain conditional on accepting it

$$\Delta w_t^{EE} = \lambda_t^e\int_{-\infty}^{\infty}\int_{w}^{\infty}\left(\tilde{w}-w\right)dF_{t+1}^e(\tilde{w})dG_t(w) = \lambda_t^e\int_{-\infty}^{\infty}\int_{-\infty}^{w}\left(w-\tilde{w}\right)dG_t(\tilde{w})\,dF_{t+1}^e(w)$$

Integrating first the inner integral by parts

$$\Delta w_t^{EE} = \lambda_t^e\int_{-\infty}^{\infty}\left(\left[\left(w-\tilde{w}\right)G_t(\tilde{w})\right]_{\tilde{w}=-\infty}^{w} + \int_{-\infty}^{w}G_t(\tilde{w})d\tilde{w}\right)dF_{t+1}^e(w)$$

[5] Integrating by parts the EE separations term in (1) gives $\int_{-\infty}^{w}(1-F_{t+1}^e(\tilde{w}))g_t(\tilde{w})\,d\tilde{w} = (1-F_{t+1}^e(w))G_t(w) + \int_{-\infty}^{w}f_{t+1}^e(\tilde{w})G_t(\tilde{w})d\tilde{w}$. The last term cancels the integrated EE hires term.

$$= \lambda_t^e \int_{-\infty}^{\infty} \int_{-\infty}^{w} G_t(\tilde{w}) d\tilde{w} dF_{t+1}^e(w)$$

Integrating the outer integral by parts

$$\Delta w_t^{EE} = \lambda_t^e \left(\left[\int_{-\infty}^{w} G_t(\tilde{w}) d\tilde{w} F_{t+1}^e(w) \right]_{w=-\infty}^{\infty} - \int_{-\infty}^{\infty} G_t(w) F_{t+1}^e(w) dw \right)$$

Since $\lim_{w \to \infty} F_{t+1}^e(w) = 1$, we have

$$\Delta w_t^{EE} = \lambda_t^e \int_{-\infty}^{\infty} \left(1 - F_{t+1}^e(w)\right) G_t(w) dw = \int_{-\infty}^{\infty} sep_t^e(w) G_t(w) dw \tag{4}$$

2.4 On-the-job wage growth

One concern with the model so far is that it abstracts from on-the-job growth in wages. Although our empirical implementation residualizes wages off a rich set of demographic characteristics that capture wage growth with experience (separately by gender, race, education groups and year) as well as with aggregate factors (state-date fixed effects), residual wages may still grow with tenure at an employer. Such wage growth may, for instance, arise if employers backload wages (Balke and Lamadon, 2022) or counter outside job offers (Postel-Vinay and Robin, 2002). Suppose that wages grow on the job at rate ξ_t. Then the law of motion for the wage distribution (1) becomes[6]

$$\begin{aligned} g_{t+1}(w) e_{t+1} &= g_t(w) e_t - \delta_t g_t(w) e_t - \lambda_t^e \left(1 - F_{t+1}^e(w)\right) g_t(w) e_t \\ &+ \lambda_t^n f_{t+1}^n(w)(1 - e_t) + \lambda_t^e f_{t+1}^e(w) G_t(w) e_t - \xi_t g_t'(w) e_t \end{aligned}$$

Integrating this and rearranging

$$\underbrace{\lambda_t^e \left(1 - F_{t+1}^e(w)\right)}_{\equiv sep_t^e(w)} = 1 - \frac{G_{t+1}(w)}{G_t(w)} \frac{e_{t+1}}{e_t} + \lambda_t^n \frac{F_{t+1}^n(w)}{G_t(w)} \frac{1 - e_t}{e_t} - \delta_t - \frac{\xi_t g_t(w)}{G_t(w)}$$

We estimate the poaching separation probability $sep_t^e(w)$ and substitute it into (3) to obtain the EE transition probability and into (4) to get the associated wage growth. We refer to this as the *OTJ*

[6] This is a discrete time approximation to a continuous time model in which (log) wages drift at rate $\xi(t)$, i.e. the evolution of the pdf $g(w, t)$ is characterized by the *Fokker-Planck* partial differential equation

$$\begin{aligned} \frac{\partial g(w,t)}{\partial t} &= -\left(\delta(t) + \lambda^e(t)\left(1 - F^e(w,t)\right) + \frac{\dot{e}(t)}{e(t)}\right) g(w,t) \\ &+ \lambda^n(t) f^n(w,t) \frac{1 - e(t)}{e(t)} + \lambda^e(t) f^e(w,t) G(w,t) - \xi(t) \frac{\partial g(w,t)}{\partial w} \end{aligned}$$

for all $t \geq 0$, subject to some initial value $g(w, 0) = g_0(w)$ for all w and $\int_{-\infty}^{\infty} g(w, t) dw = 1$ for all t.

model to distinguish it from the *baseline model* above.

3 Estimation

We now discuss how to bring the model to the data in order to estimate EE mobility.

3.1 Data sources

We use publicly available data from the CPS from 1979 to 2023 conducted by the *Bureau of Labor Statistics* (BLS) and made available by the *Integrated Public Use Microdata Series* (IPUMS) and the *National Bureau of Economic Research* (NBER).[7] The CPS is the main U.S. labor force survey, serving as the benchmark data set for labor market analyses. At the time of writing, IPUMS has incorporated ORG data through March 2023.

Every month, the CPS surveys roughly 60,000 households using a rotating panel design. Specifically, a household responds to the basic monthly survey in each month for four consecutive months, rotates out of the survey for eight months, and finally returns to answer the basic monthly survey in each month for another four consecutive months. We refer to the first four months as survey months 1–4 and the latter four months as survey months 5–8. While the CPS is designed to be representative of the U.S. population, non-random attrition necessitates the use of survey weights, which we use throughout.

For a reference week in each month, the CPS records the employment status of each household member aged 15 and older, as well as usual weekly hours for those who are employed and job search activities during the four weeks leading up to the reference week for those who are not employed.[8] Usual weekly hours are top-coded at 99 hours. In addition, basic demographic characteristics of the household member are collected.[9]

In the final month before a household either temporarily or permanently leaves the sample—i.e. in survey months 4 and 8—respondents are asked about usual weekly wage and salary earnings. Earnings are before taxes and other deductions and include overtime pay, commissions and tips. For multiple jobholders, the data reflect earnings at their main job. Earnings are top-coded at thresholds that vary throughout the sample. We refer to the first (second) wage observation month as the first (second) ORG month.

In January or February of 1983, 1987, and every other year since 1996, the CPS fielded the *Tenure Supplement*.[10] It asks employed respondents how long they have been with their current

[7] The ORG started in 1979, but it should be possible to extend our analysis back to 1976 using the May Supplements.

[8] Prior to 1994, usual weekly hours are only recorded in the ORG.

[9] Starting in 1994, households with varying hours do not report usual weekly hours on the main job. We replace these with actual hours worked on the main job.

[10] Microdata from the Tenure Supplement exist also for 1979 and 1981, while aggregate tabulations of tenure exist back to the 1960s. Prior to 1983, however, respondents were asked for tenure on their current *job*, while after 1983 they

employer. We use information from the Tenure Supplement to estimate wage growth on-the-job.

3.2 Sample selection and variable construction

We restrict attention to individuals aged 16 and older who have non-missing age, race, gender and education, and who live in one of the 50 U.S. states plus Washington D.C. We drop self-employed individuals, since weekly earnings are only recorded for wage and salary employees. Changes to individual identifiers prevent linking individuals in the following breaks: June-July 1985, September-October 1985, and May-October 1995.

Our analysis of on-the-job wage growth using ORG and Tenure Supplement data is restricted to those who are in their second ORG month when the Tenure Supplement is fielded, so that we can compute within-individual wage growth since their first ORG month. Furthermore, we condition on more than 12 months of tenure with the current employer, so that within-individual wage growth coincides with within-job wage growth.

We aggregate race to white, black and other, and education to less than high school, a high-school diploma, some college, a bachelor's degree, and more than a bachelor's degree. We top-code age at 75 years. We multiply top-coded weekly earnings by 1.5 following standard praxis.

We link individuals across survey months as well as between the basic monthly/ORG and Tenure Supplement files using the consistent ID created by IPUMS (`CPSIDV`).[11] It links individuals based on household identifiers, person identifiers, age, sex, and race.

We classify individuals in each month as wage employed, self-employed, unemployed and not in the labor force following standard practice. Since at least Clark and Summers (1979), it has been recognized that the distinction between unemployment and not in the labor force is fuzzy. Consequently, we classify all unemployed and not in the labor force as non-employed.[12]

We estimate the separation probability to non-employment δ_t as the share of wage employed individuals in month t who are non-employed in month $t+1$. We estimate the job finding probability of the non-employed λ_t^n as the share of non-employed individuals in month t who are wage employed in month $t+1$. Due to inability to link individuals in the breaks mentioned above, we cannot compute these flow rates in June 1985, September 1985, and May-September 1995.

We construct the hourly real wage as usual weekly earnings divided by usual weekly hours worked, converted to 2022 USD using the CPI. To account for the fact that different workers experience different job-ladder dynamics (Ozkan, Song and Karahan, 2023), we residualize log hourly

were asked for tenure with their current *employer*. For this reason, we focus on the post-1983 data.

[11] See `https://assets.ipums.org/_files/ipums/working_papers/ipums_wp_2023-01.pdf`.

[12] We have confirmed that we get a similarly large decline in EE mobility over time if we alternatively restrict attention to only those who are formally unemployed.

real wages off age-race-gender-education-year dummies and state-date fixed effects

$$w_{it} = \xi_{argey} + \xi_{st} + \varepsilon_{it} \tag{5}$$

Subsequently, to limit the impact of a few outliers, we winsorize residual wages at each date at the bottom and top 0.5 percentiles. Finally, we compute N cutoffs b_i such that a share i/N of observations in the pooled 1979–2023 sample fall below b_i (weighted by the survey weights). We assign $b_0 = \underline{w}$, $dw_i = b_i - b_{i-1}$ and $w_i = (b_i + b_{i-1})/2$. In practice, we set $N = 50$.

We estimate the cdf of the wage offer distribution of the non-employed $F^n_{t,i}$ as the share of hires from non-employment at date t who earn a wage of at most b_i (again weighted by the survey weights), where we define a hire from non-employment at date t, $hire^n_{t,j}$, to be any individual j who was non-employed in month $t-1$ and employed in month t

$$\begin{aligned} \widehat{F}^n_{t,i} &= \sum_j \mathbb{1}_{w_{t,j} \leq b_i} * \mathbb{1}_{hire^n_{t,j}=1} * weight_{t,j} \\ F^n_{t,i} &= \widehat{F}^n_{t,i} / F^n_{t,N} \end{aligned}$$

The cdf of the wage distribution is simply $G_{t,i} = i/N$. We approximate the densities as

$$\begin{aligned} g_{t,i} &= \frac{G_{t,i} - G_{t,i-1}}{dw_i} \\ f^n_{t,i} &= \frac{F^n_{t,i} - F^n_{t,i-1}}{dw_i} \end{aligned}$$

where $G_{i,0} = 0$ and $F^n_{i,0} = 0$.

We estimate on-the-job wage growth, ξ_t, as the change in residual wages between month t and $t-12$ among workers who remain with the same employer. Since we cannot link individuals in the breaks mentioned above, we cannot compute wage growth between June 1995, and September 1996. We set ξ_t equal to (1/12 of) the mean of this at each Tenure Supplement date, and linearly interpolate between Tenure Supplement dates as well as between these breaks to get ξ_t for all t.

3.3 Estimating EE mobility and its associated wage growth

To improve the precision of our estimates of EE mobility at date t, we pool months $t-T$ to $t+T$, where in our benchmark we set $T = 12$. That is, we obtain something akin to a 23-month centered moving average. Merging the stocks and flows from the basic monthly CPS with the offer and wage distributions from the ORG, we construct

$$y_{\tau,i} = 1 - \delta_\tau - \frac{G_{\tau+1,i}}{G_{\tau,i}} \frac{e_{\tau+1}}{e_\tau} + \lambda^n_\tau \frac{F^n_{\tau+1,i}}{G_{\tau,i}} \frac{1-e_\tau}{e_\tau} \tag{6}$$

We project $y_{\tau,i}$ on a set of dummies using OLS

$$y_{\tau,i} \quad = \quad sep^{e}_{t,i} \quad + \quad \varepsilon_{\tau,i} \tag{7}$$

Based on the estimated dummies, we compute the EE transition probability based on (3) as

$$EE_t \quad = \quad \sum_{i=1}^{N} sep^{e}_{t,i} g_{t,i} dw_i \tag{8}$$

Based on (4), we estimate average wage growth due to EE mobility as

$$\Delta w_t \quad = \quad \sum_{i=1}^{N} sep^{e}_{t,i} G_{t,i} dw_i \tag{9}$$

To estimate the OTJ model with on-the-job wage growth, we augment (6) as

$$y_{\tau,i} \quad = \quad 1 - \delta_\tau - \frac{G_{\tau+1,i}}{G_{\tau,i}} \frac{e_{\tau+1}}{e_\tau} + \lambda^n_\tau \frac{F^n_{\tau+1,i}}{G_{\tau,i}} \frac{1-e_\tau}{e_\tau} - \xi_\tau \frac{g_{\tau,i}}{G_{\tau,i}}$$

We estimate (7) with this alternative definition of the dependent variable, and construct the EE transition probability based on (12).

The EE transition probability is the product of the probability that an employed worker receives a job offer and the probability that she accepts it

$$EE_t \quad = \quad \underbrace{\lambda^e_t}_{\text{job finding probability}} \underbrace{\int_{-\infty}^{\infty} \Big(1 - F^e_{t+1}(w)\Big) dG_t(w)}_{\text{acceptance probability}} \tag{10}$$

Hence, EE mobility can fall either because workers are less likely to receive job offers or because they are less likely to accept them. To implement the decomposition (10) requires an assumption about the unobserved wage offer distribution of the employed. We follow much of the literature in assuming that the employed sample jobs from the same distribution as the non-employed, $f^e_t(w) = f^n_t(w)$. Under this assumption and using $y_{\tau,i}$ as defined in (6), we can estimate λ^e_t as

$$y_{\tau,i} \quad = \quad \lambda^e_t \Big(1 - F^n_{t+1,i}\Big) \quad + \quad \varepsilon_{\tau,i} \tag{11}$$

Based on the estimated λ^e_t, we compute an alternative EE transition probability as

$$\widehat{EE}_t \quad = \quad \lambda^e_t \sum_{i=1}^{N} \Big(1 - F^n_{t+1,i}\Big) g_{t,i} dw_i \tag{12}$$

We can also recover the average acceptance probability as $\widehat{EE}_t / \lambda^e_t$.

3.4 The role of unobserved heterogeneity

Although we control for observable demographic characteristics, hires from non-employment may differ in unobservable dimensions from their identical-looking peers who did not recently experience non-employment. Indeed, recent work argues that allowing for permanent, unobserved heterogeneity is crucial to understand worker dynamics in the data (Hall and Kudlyak, 2019; Morchio, 2020; Gregory, Menzio and Wiczer, 2021). To the extent that those who are more prone to unemployment generically earn less, we would overstate EE mobility, because we attribute the entire gap between the wage and offer distributions to EE mobility.

To address this concern, we exploit the fact that we can observe prior wages. Specifically, the basic monthly survey merged with the ORG allows us to link hires from non-employment in survey month 6–8 to their lagged residual wage in survey month four, i.e. 10–12 months earlier. We compute the lagged residual wage of hires from non-employment relative to those not hired from non-employment.[13] Note that we do not know an individual's prior employment status in survey month five, hence its exclusion.

Figure 1 plots the average previous residual log wage of hires from non-employment relative to all workers.[14] Hires from non-employment earned 5–15 percent lower residual wages 10–12 months earlier. This pattern is consistent with hires from non-employment being negatively selected in unobservable dimensions. It does not, however, display much of a time trend, suggesting that such selection did not change over this period.

To more formally adjust for selection, we further residualize a worker's current residual wage off her prior residual wage. We refer to this as the *unobservables model*. The main drawback of this specification is that it cuts the sample by roughly 60 percent, since it requires respondents to be employed in both the first and second ORG month.

4 A Historical Account of EE mobility

This section presents a complete historical account of gross worker flows in the U.S. between 1979 and 2023, highlighting in particular the evolution of the EE transition probability. We begin by presenting our estimates for EE mobility since 1979. We then discuss the implications of our results for gross worker flows and for wage growth. After that, we move on to describing heterogeneity in the evolution of the EE rate across different demographic groups.

[13] Although we residualize wages in survey month four controlling for time effects, we do this prior to restricting attention to those with valid wage employment in survey months 6–8. Non-random attrition necessitates expressing lagged residual wages of hires from non-employment in survey months 6–8 relative to lagged residual wages of all workers in survey months 6–8.

[14] A potential drawback of this approach is that it conditions on wage employment at the time of the first ORG survey. An alternative is to use wages in the previous calendar year from the ASEC, which only imposes that the respondent worked for pay at some point in the previous calendar year. We find similar results using this alternative approach, but we prefer using the ORG as baseline because it is larger.

Figure 1: Previous residual log wages of hires from non-employment relative to all workers measured 10–12 months earlier.

4.1 EE mobility

According to the baseline model in Figure 2, 1.5 percent of workers made an EE transition toward a higher paying job per month in the 1980s. The OTJ model that allows for on-the-job growth in residual wages indicates a slightly lower level of EE mobility, because it does not attribute all positive wage changes to EE moves. The difference, however, is small, driven by the fact that on-the-job residual wage growth with tenure is second-order. Adding also the previous residual wage as a control for unobservable characteristics further lowers the level of EE mobility, especially at the beginning of our sample. The reason is that we attribute some of the gap between the wage offer and overall wage distribution to recently non-employed workers being negatively selected (recall Figure 1).

All models indicate a secular decline in EE mobility over the past decades. The baseline model implies a 50 percent fall in the EE transition probability from 1979 to 2023. All models find a particularly pronounced decline between 1985 and 2000. Our estimates also indicate a brief reversal in the decline during the early years of the pandemic (Birinci et al., 2022; Caratelli, 2022) and the recovery that followed, but that the EE transition probability has continued to decline since then.

Figure 3 contrasts our structural estimate of EE mobility with the fraction of employed workers in month t who are employed with a different employer in month $t+1$. For brevity, we focus on the structural estimate in the baseline model (solid black). The raw series from the CPS shows a pronounced decline in EE mobility during the 2000s (dashed light blue). Fujita, Moscarini and Postel-Vinay (Forthcoming) argue, however, that changes in non-response rates in the 2000s bias the raw CPS series toward an excessively large decline. Consistent with this view, our structural estimate as well as the raw series from the *Survey of Income and Program Participation* (SIPP) (dotted

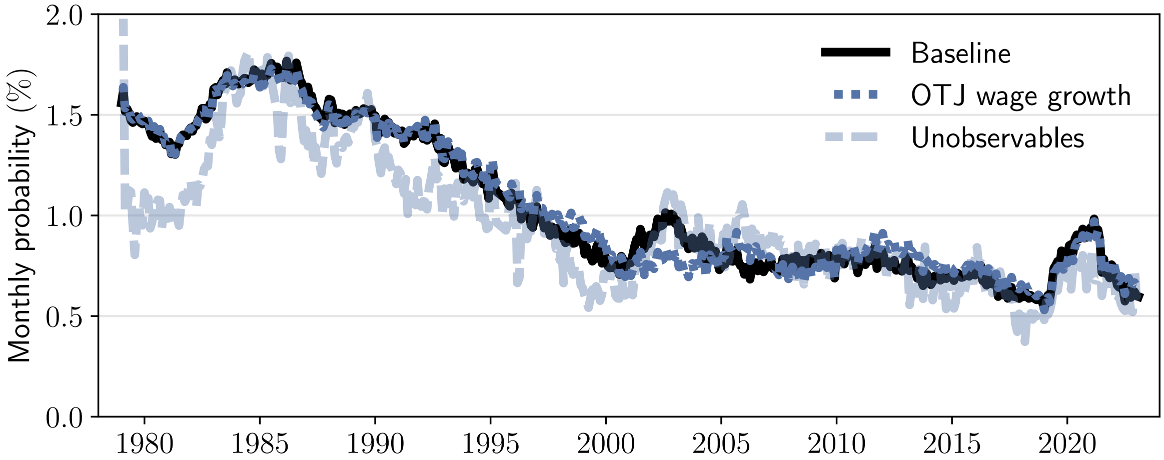


Figure 2: Estimated EE transition probability in the baseline model (black), the OTJ model with on-the-job wage growth (dark blue dotted), and the unobservables model with controls also for the wage 10–12 months earlier (light blue dashed).

dark blue) shows a more moderate decline in EE mobility during the 2000s.[15]

Contrasting our estimate with the SIPP, it is evident that a large share of EE mobility is *not* to higher paying jobs, consistent with the findings in Tjaden and Wellschmied (2014) and Sorkin (2018). This conclusion is validated by the *SIPP (up)* series, which plots the monthly EE transition probability to higher paying jobs in the SIPP (solid dark blue).[16] It is reassuringly similar to our estimated EE series, both in levels and changes during the years for which the SIPP is available.

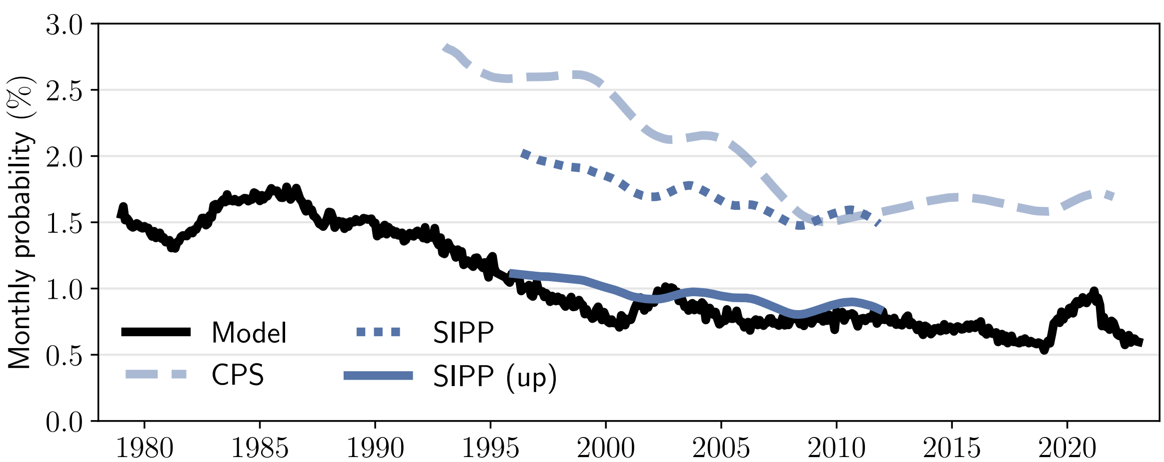


Figure 3: Comparison between the EE transition probability implied by the baseline model (black), the raw overall EE transition probability in the CPS (dashed light blue) and the SIPP (dotted dark blue), and the raw EE transition probability towards higher-paying jobs in SIPP (solid dark blue).

[15] Consistent SIPP data are available from 1996 to 2013. We impose exactly the same sample selection criteria in the SIPP as in the CPS.

[16] Because it does not collect wages in consecutive months, we cannot construct this outcome in the CPS.

It is informative to highlight what features of the data lead us to infer that EE mobility declined. To that end, we note that in steady-state, outflows from and inflows into employment coincide, $\lambda_t^n(1-e_t) = \delta_t e_t$. Hence, if we assume that the labor market at date t is in steady-state, the law of motion for the wage distribution (2) simplifies to

$$\lambda_t^e\left(1 - F_{t+1}^e(w)\right) = \lambda_t^n \frac{F_{t+1}^n(w)}{G_t(w)} \frac{1-e_t}{e_t} - \delta_t = \delta_t \frac{F_{t+1}^n(w) - G_t(w)}{G_t(w)} \tag{13}$$

Integrating (13) against the distribution of employment and taking logs gives

$$\ln\left(EE_t\right) = \underbrace{\ln\left(\delta_t\right)}_{\text{separation probability channel}} + \underbrace{\ln\left(\int_{-\infty}^{\infty} \frac{F_{t+1}^n(w) - G_t(w)}{G_t(w)} dG_t(w)\right)}_{\text{offer channel}} \tag{14}$$

Hence in a statistical sense, we can attribute our inferred decline in EE mobility to one of two channels: a change in the separation probability to non-employment—the *separation probability channel*—and a change in the average gap between the offer and the wage distribution, the *offer channel*. We stress that this decomposition should be interpreted in a purely statistical sense—according to the model, a change in δ_t would *result* in a change in the employment distribution.

Figure 4 implements the steady-state decomposition (14) of the EE transition probability into changes in the separation probability to non-employment and changes in the gap between the offer and wage distributions. Although this incorrectly assumes that the economy is in steady-state, in practice it seems to matter little, in the sense that the estimated overall change in EE mobility is similar whether we use the full dynamic model (solid black) or impose the steady-state assumption (solid blue). For a fixed average gap between the wage and offer distributions, the observed decline in the separation probability to non-employment over this period implies that EE mobility must have declined. Conversely, holding fixed the separation probability to non-employment, the shrinking gap between the offer and wage distributions must be the result of lower EE mobility. In a statistical sense, this decomposition shows that a shrinking gap between the offer and wage distributions is the main reason we infer a decline in EE mobility. That being said, the separation channel remains important in terms of accounting for some episodes, such as the increase in the EE transition probability in the Pandemic recession.

4.2 Worker flows, job flows and churn

While our finding of a decline in EE mobility mirrors the well-known decline in job reallocation over this period (Davis and Haltiwanger, 2014; Decker et al., 2016), we stress that it does not follow mechanically from the latter. To see why, note that the overall worker reallocation rate—the sum of hires and separations divided by employment—can be written as the sum of *job reallocation* and

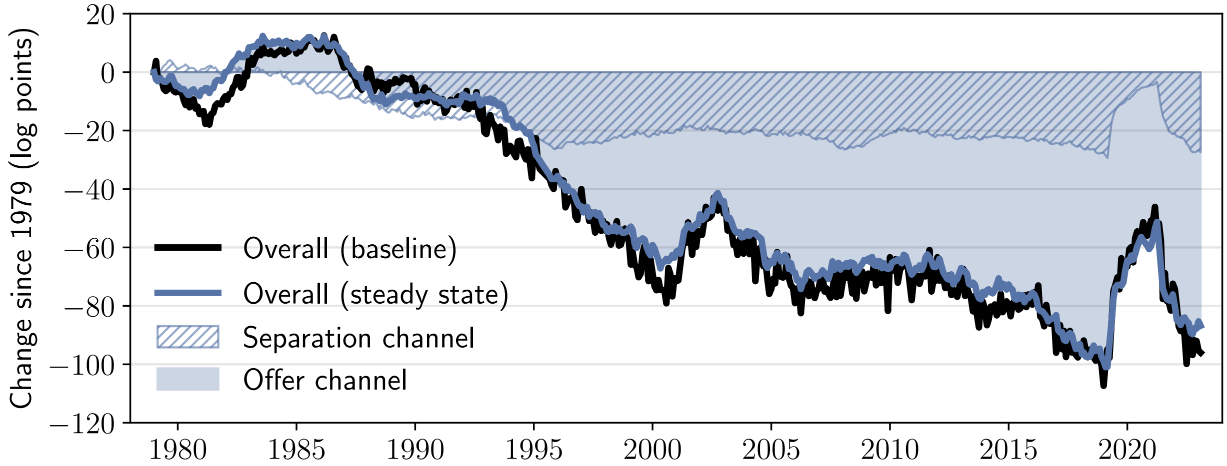


Figure 4: Decomposition of log-EE mobility decline into the separation probability channel and the offer channel based on (14).

worker churn—worker flows over and above what is necessary to reallocate jobs

$$\underbrace{WR_t}_{\text{worker reallocation}} = \underbrace{2 \times EE_t}_{\text{poaching flows}} + \underbrace{\delta_t}_{\text{separations to non-employment}} + \underbrace{\lambda_t^n \frac{1-e_t}{e_t}}_{\text{hires from non-employment}} \tag{15}$$

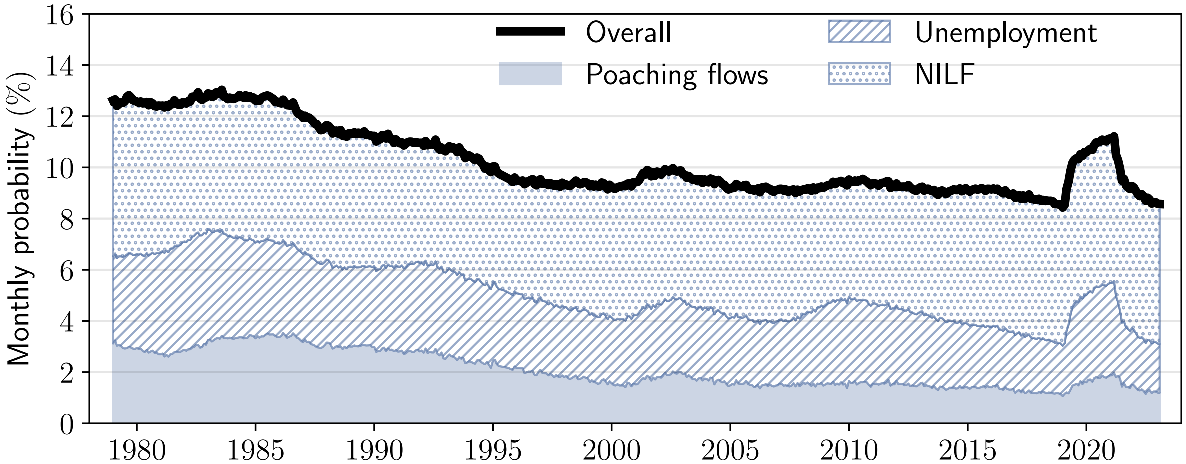
$$= \underbrace{JR_t}_{\text{job creation + job destruction}} + \underbrace{Churn_t}_{\text{replacement hiring}} \tag{16}$$

Worker reallocation is at least as large as job reallocation, since whenever a job is reallocated across firms, a worker necessarily switches employer. It may be higher because a job would remain with the firm whenever it hires a new worker to replace someone who left.

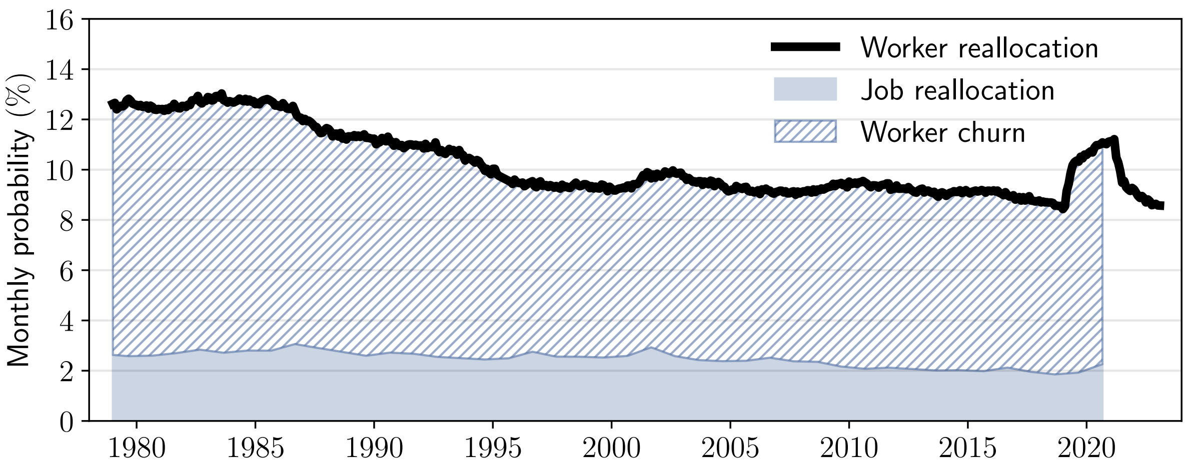
Figure 5 decomposes overall worker reallocation following (15)–(16) (using the baseline model). During the 1980s, EE mobility toward higher paying jobs constituted roughly a quarter of overall worker flows. Flows in and out of unemployment accounted for about 30 percent of overall flows, with the remainder of worker reallocation taking place through non-participation. Because we do not adjust for recalls, which are a significant share of flows into and out of non-employment (Fujita and Moscarini, 2017; Hall and Kudlyak, 2022), this likely understates the role of EE mobility for overall worker reallocation. Moreover, a nontrivial share of workers make EE transitions toward lower paying jobs (Tjaden and Wellschmied, 2014; Sorkin, 2018). Accounting for these would boost the importance of EE transitions, but lower the share of EE transitions toward higher paying jobs. Finally, the CPS is known to suffer from labor force status classification error, which inflates gross flows between employment and non-employment (Abowd and Zellner, 1985). Accounting for this would increase the relative importance of EE transitions. Disregarding these measurement issues, we find that worker reallocation is four times as large as job reallocation.[17]

[17]The BDS reports in year t the job reallocation between March in year $t-1$ and March in year t. We divide this by 12

Poaching flows declined substantially as a share of total worker flows over the past 45 years, reaching an all time low of about 15 percent today (panel a). Flows in and out of unemployment also fell, while flows in and out of non-participation are at about the same level today as they were in 1980. Combining these trends, the overall worker reallocation rate fell from over 12 percent of employment per month in the 1980s to nine percent today, with poaching flows responsible for almost half of this decline. Although some of the fall in worker reallocation is accounted for by the well-documented decline in job reallocation (Davis and Haltiwanger, 2014), most of the decline is accounted for by decreasing worker churn (panel b).



(a) Worker relocation decomposition in poaching and non-employment flows as stated in equation (15).



(b) Worker reallocation decomposed in job reallocation and churn following equation (16).

Figure 5: Overall worker reallocation decomposed following (15)–(16). Monthly job reallocation here is the annual rate divided by 12 (available from the Census Bureau's *Business Dynamics Statistics* until 2021).

to get a proxy for the job reallocation rate in September in year $t-1$, and linearly interpolate for the months in between September in year $t-1$ and year t.

4.3 Implications for wage growth

A recent literature stresses the central role of EE mobility for wage growth (Karahan et al., 2017; Moscarini and Postel-Vinay, 2017; Ozkan, Song and Karahan, 2023; Tanaka, Warren and Wiczer, 2023). We would hence expect the decline in EE mobility to contribute to weaker wage growth.

Figure 6 confirms this intuition based on equation (4), finding a decline in monthly residual wage growth due to EE mobility of about 0.15 percentage points from the 1980s until now. Allowing for on-the-job growth in residual wages has only a small effect on both the level and the trend, due to the fact that such wage growth is uniformly small. While residualizing a worker's current wage also off her prior wage has little impact on EE mobility, it lowers the estimated wage gain associated with EE mobility. Furthermore, it reduces the estimated decline in wage growth due to EE mobility to show a decline from about 0.25 percentage points monthly to 0.15 percentage points today, or about a one percentage point decline in annual wage growth.

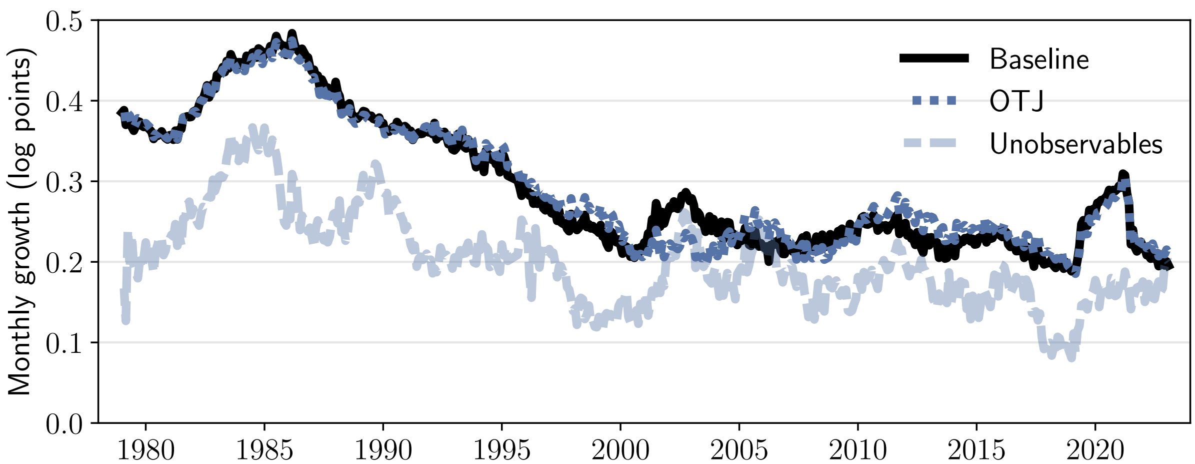


Figure 6: Monthly growth in residual wages associated with EE mobility in the baseline model (black), the OTJ model with on-the-job wage growth (dark blue dotted), and the unobservables model with controls also for the wage 10–12 months earlier (light blue dashed).

Figure 7 uses the OTJ model to provide an estimate of overall residual wage growth of continuously employed workers, as well as residual wage growth on-the-job. The latter is uniformly small, consistent with earlier findings (Molloy et al., 2016). Consequently, the decline in overall wage growth once we include on-the-job wage growth, shown in gray, tracks closely wage growth due to EE mobility. For reference, we also include wage growth upon EE transitions to higher paying jobs in the SIPP.[18] That is, the solid blue line plots the product of the median percent change in wages between month $t-1$ and $t+1$ for workers who made an EE transition in month t times

[18]We residualize wages in the SIPP off demographic characteristics the same way as in the CPS, subsequently winsorize wages at the bottom and top 0.5 percentiles, and finally bin them into the same N bins as in the CPS. The only difference we make in the SIPP is that we use median instead of average wages in order to limit the impact of a few outliers (using averages instead results in the same changes over time, but generally a higher level of wage growth).

the average EE transition probability in month t.[19]

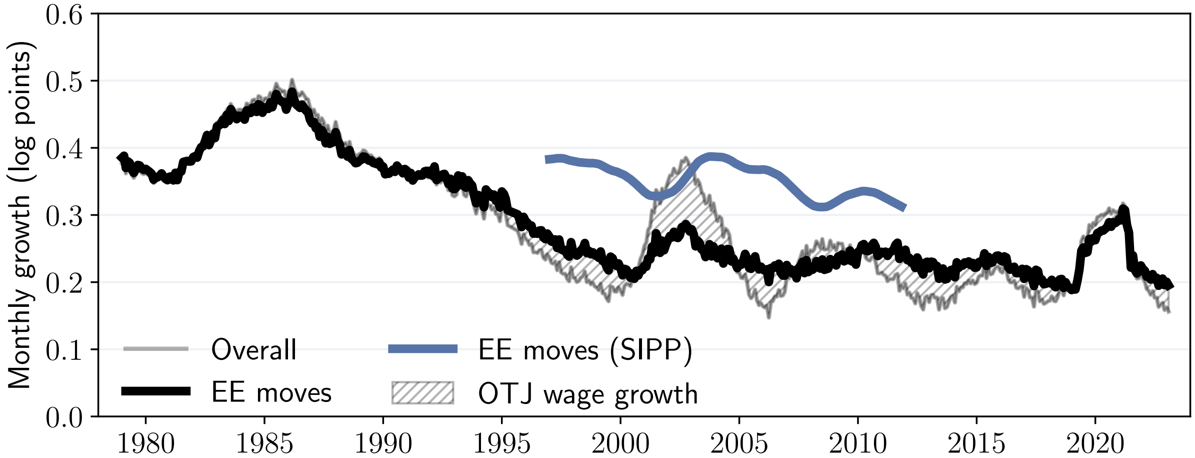


Figure 7: Monthly growth in residual wages associated with EE mobility in the OTJ model and in the SIPP. The SIPP series shows the product of the median percent wage gain upon an EE transition times the monthly probability of making an EE move (both are conditional on moving to a higher paying job).

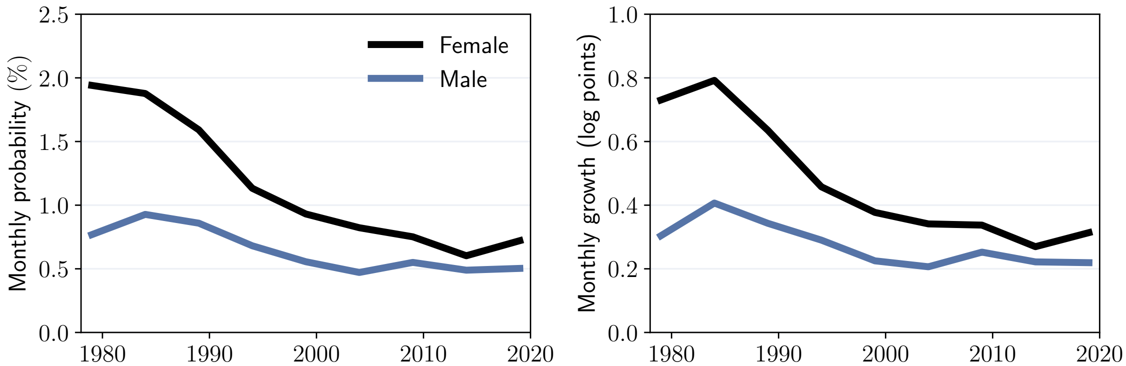
4.4 Who experienced the largest declines?

Because different groups of workers display different labor market outcomes (Elsby, Hobijn and Şahin, 2010), it is natural to ask whether the decline in EE mobility was more pronounced in certain sub-populations. If so, the aggregate decline could be the result of shifts in the composition of the workforce toward sub-populations that are generically less dynamic. In this section, we dissect the decline in EE mobility by gender, race, education and age. Given our focus on secular trends, to reduce noise we increase the smoothing to $T = 30$ months so that we obtain five-year averages and we reduce the number of bins for wages to $N = 10$.[20]

Gender. Figure 8 shows that EE mobility and the associated wage growth were larger for women throughout the period, which coincided with women making rapid advancements in the labor market (Goldin, 2014). However, in levels both measures fell by more for women over time, *ceteris paribus* contributing to slower convergence in the gender pay gap (Blau and Kahn, 2006; Blair and Posmanick, 2023). Also in relative terms, the decline in EE mobility toward higher paying jobs was more pronounced for women, but the difference relative to men is smaller.

[19] We take the median instead of the average to limit the impact of a few outliers. Using the average delivers a higher level of wage growth, but a similar time trend.

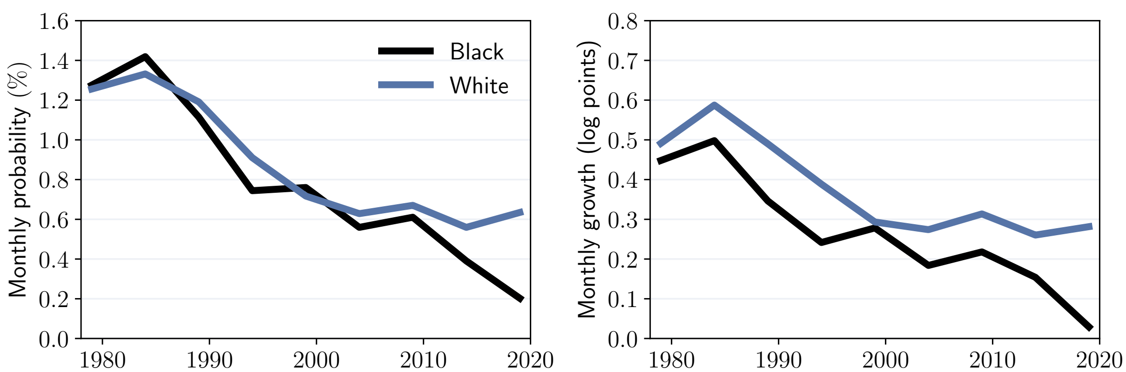
[20] It makes little difference if we set $N = 10$, $N = 20$, $N = 50$ or $N = 100$ for both the aggregate results above as well as those within sub-population that we present here. With a high number of bins, however, we end up estimating a negative poaching separation rate in some bins at some points in time, presumably due to sampling error. While the EE transition probability remains positive since it is the average across all bins, it is nevertheless not economically sensible to have a negative poaching separation rate. For this reason, we prefer to set a lower number of grid points.



(a) EE mobility rate. (b) Average wage growth associated with EE mobility.

Figure 8: EE transition probability and associated wage growth by gender. All mobility is to higher-paying jobs.

Race. According to Figure 9, white and black workers had similar rates of EE mobility in the 1980s (panel a), yet white workers experienced higher wage growth associated with EE mobility (panel b). The reason is that white workers experience greater wage growth conditional on an EE transition. Over time, EE mobility and its associated wage growth declined for both races. Yet the decline was more pronounced for black workers, particularly after 2000. This suggests that changes in EE mobility could account for some of the increased racial wage gap over this period (Wilson and Darity Jr., 2022).

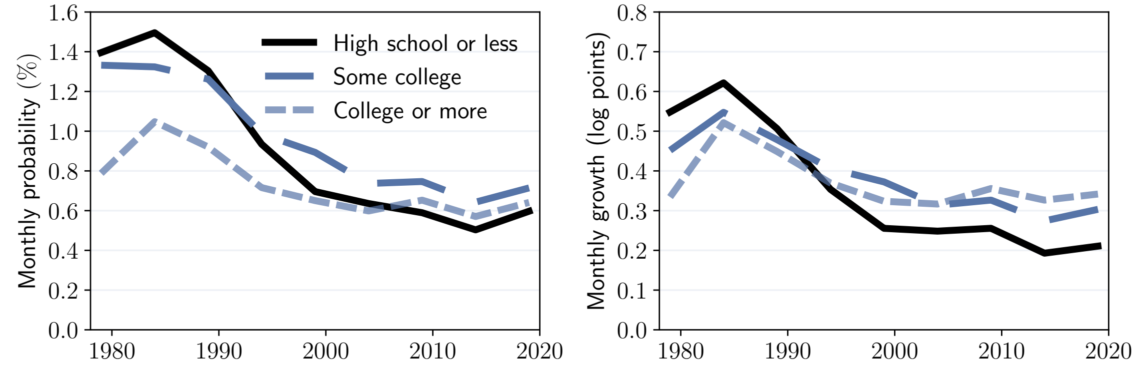


(a) EE mobility rate. (b) Average wage growth associated with EE mobility.

Figure 9: EE transition probability and associated wage growth by race. All mobility is to higher-paying jobs.

Education. Workers without a college degree were *more* likely than their peers with a degree to make an EE transition toward a higher paying job in the first half of our sample (Figure 10). This supports the findings by Haltiwanger, Hyatt and McEntarfer (2018). Since then, the job ladder for those with at most a high-school degree experienced a dramatic collapse, so that today they are less likely to make an EE transition toward a higher paying job than their more educated peers.

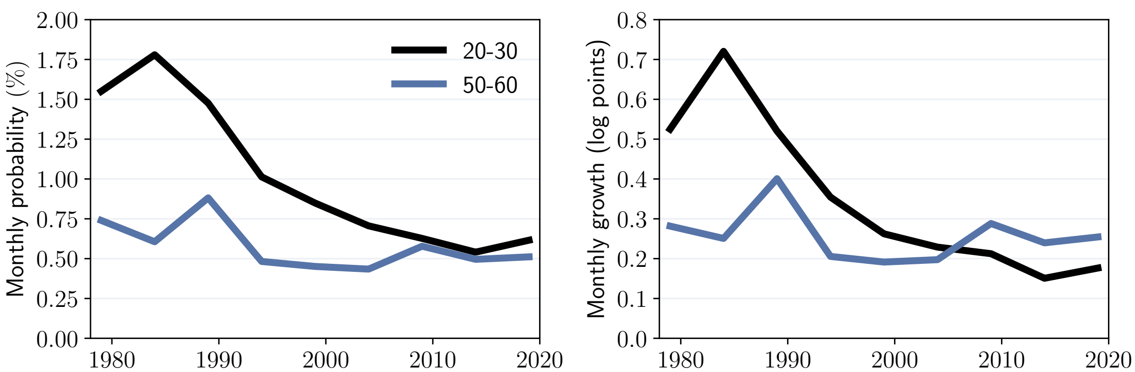
These trends in EE mobility are reflected in changes in wage growth associated with EE mobility.



(a) EE mobility rate. (b) Average wage growth associated with EE mobility.

Figure 10: EE transition probability and associated wage growth by education. All mobility is to higher-paying jobs.

Age. Figure 11 shows that young workers consistently have a higher EE transition probability than their older peers, consistent with the findings in Haltiwanger, Hyatt and McEntarfer (2018). Over time, however, young workers experienced a much more pronounced decline in EE mobility. Bosler and Petrosky-Nadeau (2016) reach a similar conclusion in the SIPP over the shorter period 1996–2013. These trends are particularly concerning given the importance of EE mobility for young workers' career advancement (Topel and Ward, 1992). Indeed, panel b shows a sharp deceleration in wage growth associated with EE mobility for young workers.



(a) EE mobility rate. (b) Average wage growth associated with EE mobility.

Figure 11: EE transition probability and associated wage growth by age. All mobility is to higher-paying jobs.

Cohort. The patterns in Figure 11 are suggestive of a cohort component to the decline in EE mobility, whereby new cohorts are systematically less dynamic than their older peers. To investigate this hypothesis further, Figure 12 plots the age profile of EE mobility for the full sample (solid black), the 1955 cohort (dashed), the 1965 cohort (dash-dotted), and the 1975 cohort (dotted light). For reference we include also the EE transition probability toward higher paying jobs for the full sample in the SIPP in solid blue. Consistent with earlier findings, EE mobility declines with age up to around age 50, and stabilizes after that. Moreover, more recent cohorts display an overall lower EE transition probability at all ages.

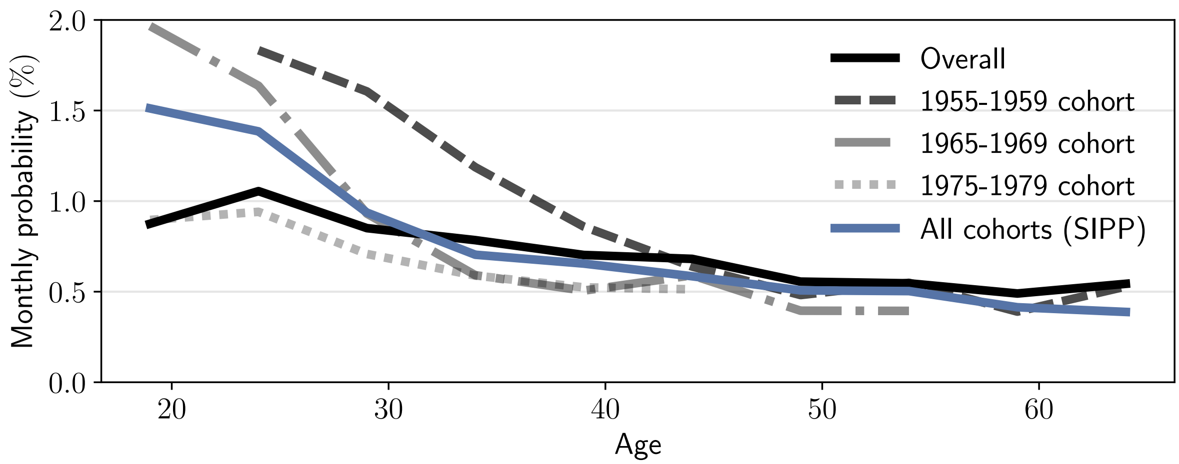


Figure 12: Age profile of EE transition probability estimated in the model for all cohorts (solid black), 1955 cohort (dashed), 1965 cohort (dash-dotted), and 1975 cohort (dotted). In solid blue is the SIPP equivalent measure. All mobility is to higher-paying jobs.

To quantify the contributions of time, age and cohort effects toward the overall decline, we build on a literature doing the same for wages (Heckman, Lochner and Taber, 1998; Lagakos et al., 2018). Specifically, we project the EE transition probability at time t for age group a of cohort c on time fixed effects (ϕ_t), age fixed effects (ψ_a) and cohort fixed effects (ξ_c)[21]

$$EE_{t,a,c} \quad = \quad \phi_t \; + \; \psi_a \; + \; \xi_c \; + \; \varepsilon_{t,a,c} \tag{17}$$

As is well-known, without a restriction, equation (17) cannot be identified due to perfect collinearity between time, age and cohort effects. Motivated by the theoretical prediction that mobility should settle at some age, we impose the restriction that mobility does not change between ages 54 and 68.[22] This assumption is sufficient to separate changes in the effect of time, age and cohort.

Figure 13 decomposes the overall decline in EE mobility into the role of time, age and cohort effects. Because older workers are less likely to make an EE transition and the U.S. workforce aged substantially over this period, the age effects account for some of the aggregate decline in EE mobility. Time effects are behind most of the initial increase in EE mobility as well as most of the decline in the late 1980s and early 1990s. Since 2005, however, they contributed to an *increase* in EE mobility, *ceteris paribus*. Hence, most of the secular decline in the aggregate EE transition

[21]While we estimate (17) in levels, substantively similar results hold if we alternatively estimate it in logs.
[22]Similar results hold if we alternatively impose that mobility is flat between ages 54–63, 49–63 or 49–58.

probability is accounted for by the fact that new cohorts are less dynamic than their older peers.

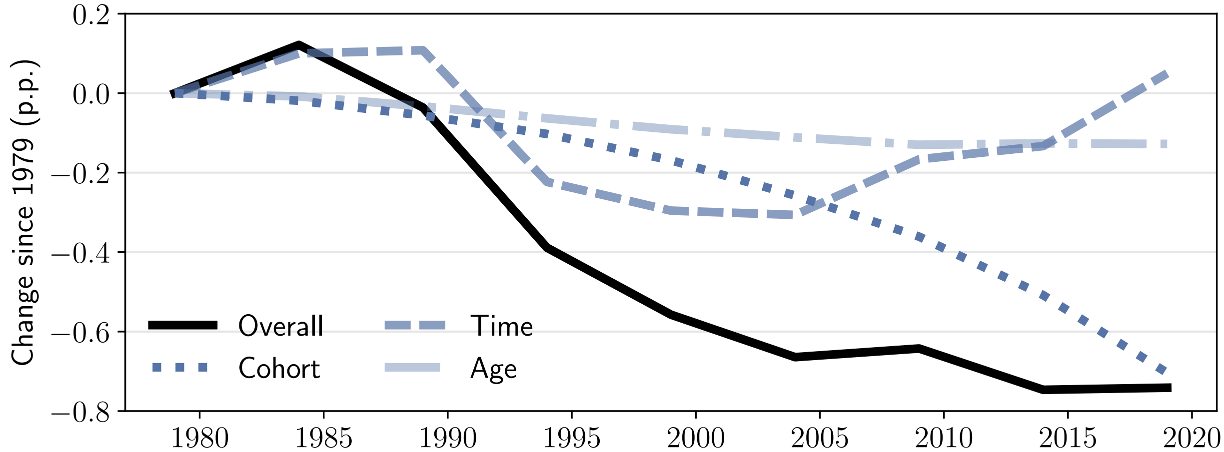


Figure 13: Change in EE transition probability overall (solid) and broken down in its time (dashed), age (dash-dotted), and cohort (dotted) components.

5 Why did EE mobility decline?

In this section, we explore potential forces behind the decline in EE mobility. We first provide evidence that the decline is unlikely to be driven by an improvement in workers' existing matches. Second, we argue that it is likely not the result of a worsening of matching efficiency. Finally, we highlight a link between increases in labor market concentration and declines in EE mobility.

5.1 Are workers better matched today?

One hypothesis is that EE mobility declined because workers are better matched today, so that workers make fewer transitions in search of better matches (Mercan, 2017; Pries and Rogerson, 2022). We provide two pieces of evidence that caution against this interpretation. First, Figure 14 shows the wage gain *conditional* on making an EE transition according to both the model and the SIPP data.[23] The latter is for workers moving to higher paying jobs. Both the structural estimate and the raw SIPP measure indicate substantial wage growth associated with EE mobility toward higher paying jobs. According to both, the average wage gain conditional on moving to a higher paying job increased over time. We interpret the fact that returns to mobility rose to suggest that the decline in mobility is not the result of workers being better matched in their current jobs.

Second, recall from (10) that under the assumption the employed and non-employed sample from the same wage offer distribution, the EE transition probability can be decomposed into the

[23] As we noted above, we use median instead of means in the SIPP in order to limit the impact of a few outliers. Using the average instead results in a similar increase over time, but a higher level of wage growth.

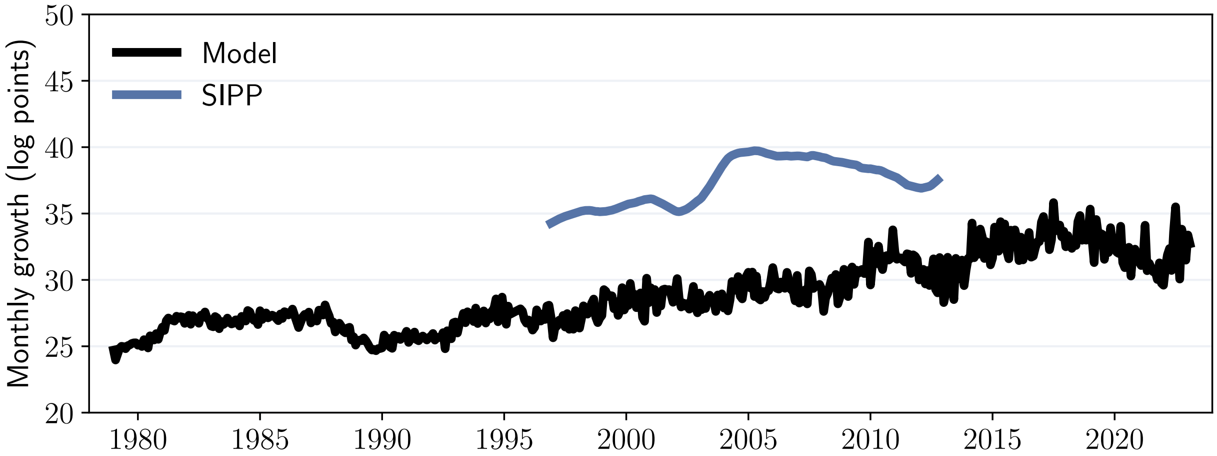


Figure 14: Wage growth conditional on switching to a higher-paying employer in model (black) and in the SIPP (blue).

probability that a worker receives an outside job offer versus the probability that she accepts it

$$\ln \widehat{EE}_t = \underbrace{\ln\left(\lambda_t^e\right)}_{\text{job finding probability}} + \underbrace{\ln\left(\int_{-\infty}^{\infty}\left(1-F_{t+1}^n\left(w\right)\right)dG_t\left(w\right)\right)}_{\text{acceptance probability}}$$

Figure 15 implements this decomposition. For reference, we also include the EE transition probability under the benchmark model that does not impose that the employed sample from the same offer distribution as the non-employed. Since the mid-1980s, workers have become slightly *more* likely to accept extended offers. Molloy et al. (2016) similarly argue based on the lack of a long-run trend in starting wages that workers are not better able to immediately locate a good match today. Hence, EE mobility is lower today due to a lower arrival probability of outside job offers.

5.2 Did the labor market become worse at matching workers and firms?

To understand the potential forces behind the decline in the job finding probability of the employed, it is useful to extend the partial equilibrium model of Section 2 in general equilibrium via the following standard assumptions. First, suppose that the employed search with search efficiency $\phi_t \geq 0$ relative to the non-employed. Second, let firms advertise jobs subject to some cost. Third, postulate a homogeneous of degree one aggregate matching function $\mathcal{M}_t(V,S)$ that gives the meeting probabilities as a function of the total number of vacancies V and effective number of searching workers S. Then the job finding probabilities of the non-employed and employed are

$$\lambda_t^n = \mathcal{M}_t\left(\frac{V_t}{S_t},1\right), \qquad \text{and} \qquad \lambda_t^e = \phi_t\mathcal{M}_t\left(\frac{V_t}{S_t},1\right)$$

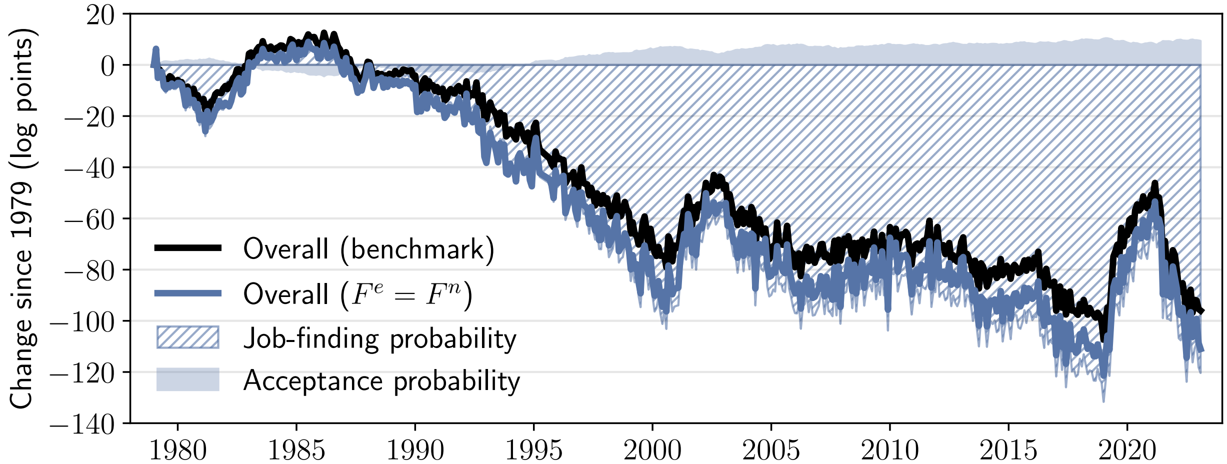


Figure 15: Decomposition of log-EE mobility decline into the job-finding probability and the acceptance probability. In solid black is the benchmark EE transition probability. In solid blue the equivalent under the assumption that employed and unemployed draw offers from the same distribution (F^n); this is the series that the decomposition is based upon.

Consequently, changes in, for instance, the matching function, aggregate vacancies, or aggregate search intensity have a proportional impact on the job finding probabilities of the employed and non-employed. To gain insights into the sources of the changes in EE mobility, it is hence useful to also study changes in the non-employment-to-employment transition probability.

Figure 16 shows that the job finding probability of the employed fell by much more than that of the non-employed (both series are expressed in log deviations relative to their values in 1979). From the perspective of benchmark equilibrium theories of the labor market, it is hard to reconcile these divergent patterns as the result of, for instance, a worsening of matching efficiency or less job creation by firms. Instead, our results point to forces that disproportionately reduced the job finding probability of the employed. For instance, the increasing prevalence of non-competes could have discouraged job shopping by the employed (Gottfries and Jarosch, 2023). Alternatively, increasing labor market concentration could have reduced outside job options for the employed, with less of an effect on the job finding prospects of the non-employed (Bagga, 2023; Jarosch, Nimczik and Sorkin, 2024). We offer some further evidence consistent with this hypothesis below.

5.3 Labor market concentration

One possible factor behind the larger decline in the job finding probability of the employed relative to the non-employed is increasing labor market concentration that reduced the opportunities for job shopping (Bagga, 2023; Jarosch, Nimczik and Sorkin, 2024). For instance, Jarosch, Nimczik and Sorkin (2024) argue that employers can commit to not rehire workers who separate from them, thus reducing outside options for employed workers relative to the non-employed.

To investigate this hypothesis, we re-estimate EE mobility across the nine Census divisions of

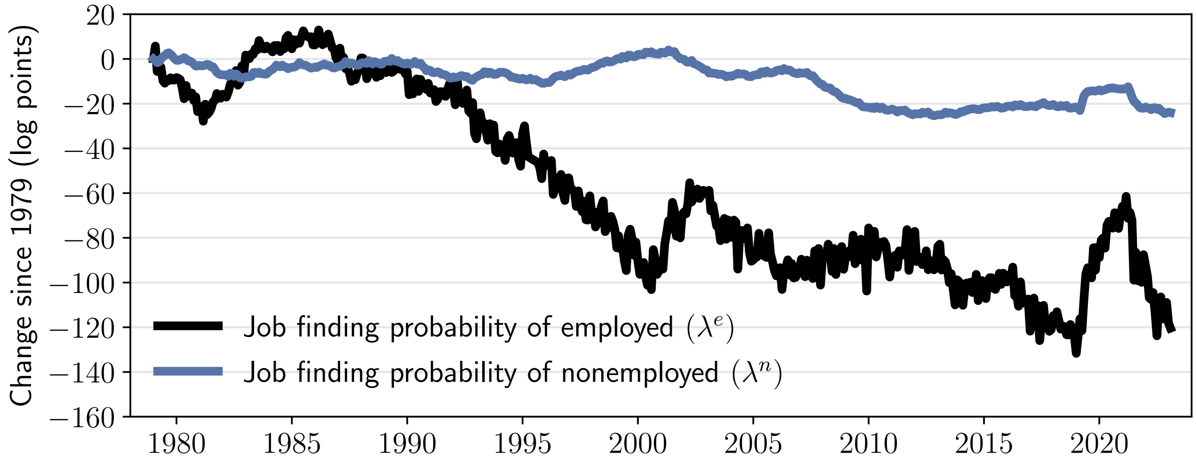


Figure 16: Log point change in the the job finding probability out of employment (blakc) and non-employment (blue). All changes are since 1979.

the U.S. within five year bins. We merge the resulting EE transition probability with data on the ratio of firms to workers from the BDS, which covers essentially all private sector employment between 1978 and 2021. Given that we bin the data into five year bins, we restrict attention to 1979–2018, which offers the additional benefit that it avoids the Pandemic recession and recovery.

Figure 17 plots the EE transition probability and ratio of firms to workers for each Census division over time. Both series are in logs and expressed relative to the average across all Census divisions at a point in time (equivalent to residualizing off time fixed effects) and the Census division mean over the entire sample period (equivalent to taking out division fixed effects). Divisions that experienced greater increases in market concentration than the rest of the U.S. saw disproportionate declines in EE mobility.

Figure 18 offers an alternative way to visualize the correlation between market concentration and EE mobility. It plots long log differences of the ratio of firms to workers and various labor market outcomes between 1984–1988 and 2014–2018 (we drop the first five years as they appear to be somewhat of an outlier). Regions that experienced larger increases in labor market concentration saw greater declines in EE mobility (panel a) as well as its associated wage growth (panel b) and the job finding probability of the employed (panel c). In contrast, the correlation with changes in the job finding probability of the non-employed is much weaker (panel d).

We can investigate these conditional correlations more formally by projecting various labor market outcomes at the Census division-five year period level ($y_{d,p}$) on the ratio of firms to worker ($c_{d,p}$), controlling for division fixed effects (ξ_d) and period fixed effects (ϕ_p)

$$y_{d,p} = \beta c_{d,p} + \xi_d + \phi_p + \varepsilon_{d,p} \tag{18}$$

Both the dependent and independent variables are in logs. Although we find these conditional

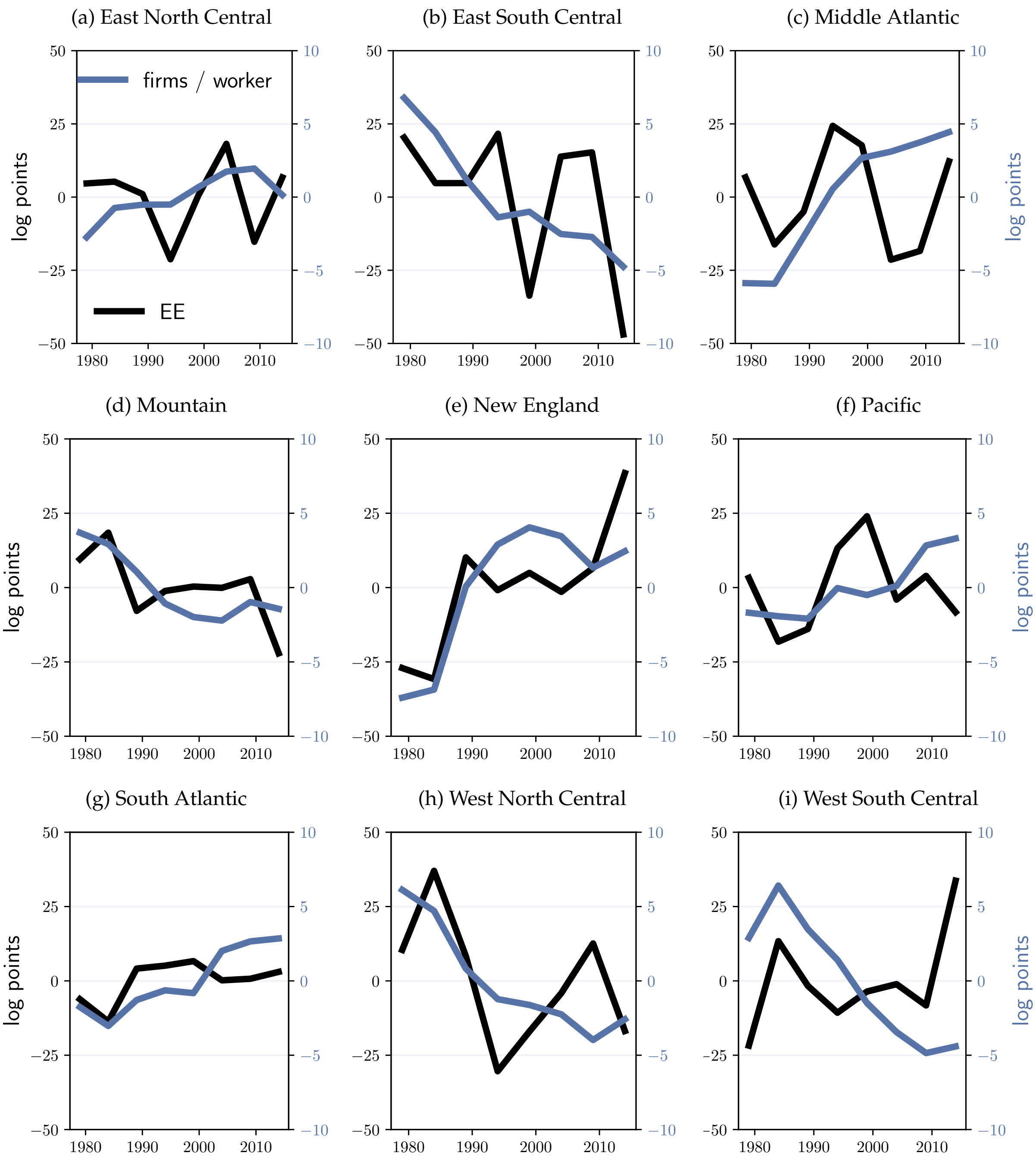


Figure 17: Estimated EE transition probability and market concentration as measured by the ratio of firms to workers over time by U.S. Census division. All mobility is to higher-paying jobs.

correlations interesting, we stress that they should not be interpreted to reflect a causal effect.

Table 1 provides the results from estimating (18).[24] A one percent increase in the number of firms per worker is associated with a 1.8 percent increase in the EE transition probability. It is

[24]For completeness, we include standard errors, but we do not want to assign much weight to these given the lack of clustering at the division level (we only have nine divisions).

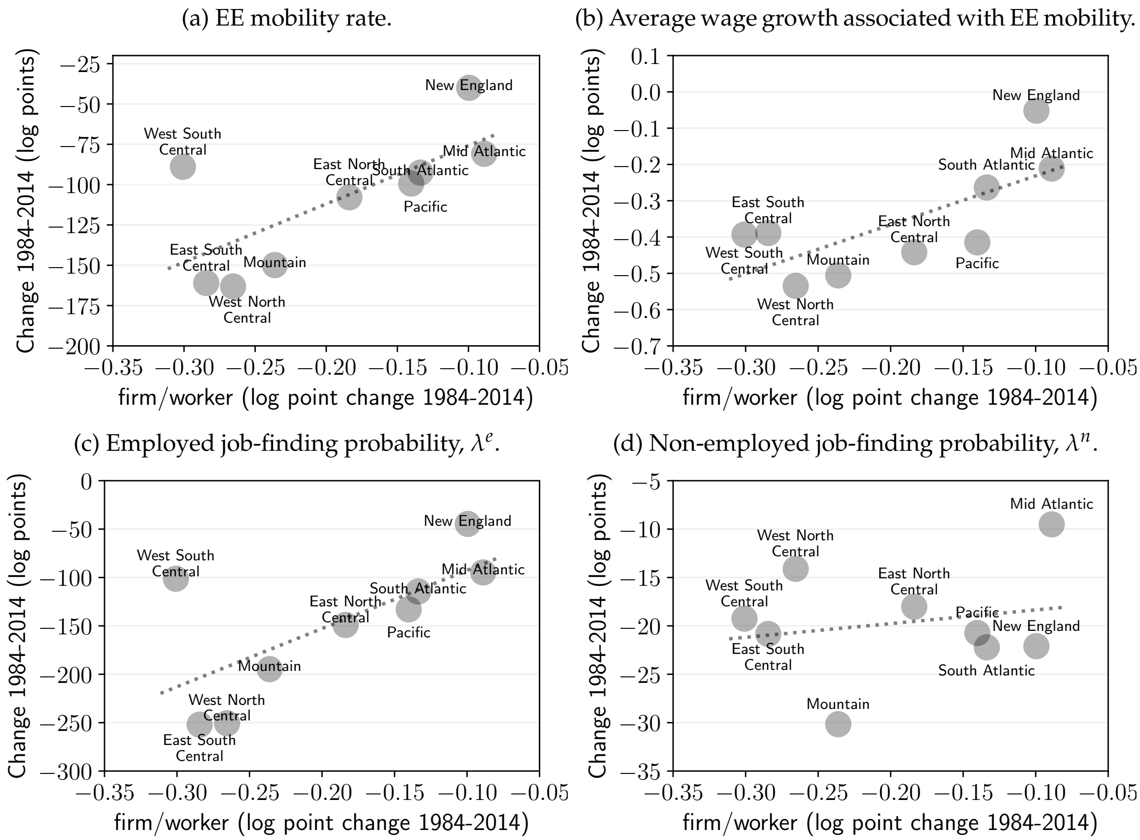


Figure 18: Changes in EE transition probability (a), associated wage growth (b), job-finding probability for the employed (c), and job-finding probability for the non-employed (d) by market concentration as measured by number of firms per worker. All outcomes are in logs and graphs show long-dfferences within a Census division between 1984-1988 and 2014–2018. All mobility is to higher-paying jobs.

associated with an 0.008 percent increase in annual wage growth due to EE mobility. The increase in EE mobility is not the result of a higher acceptance probability, but a higher arrival probability of outside job offers. Also the job finding probability of the non-employed is higher, but the magnitude is substantially smaller than for the job finding probability of the employed. Qualitatively, these results are consistent with the aggregate time trends in the U.S.

To provide a sense of their quantitative magnitudes, Figure 19 uses the cross-sectional estimates to predict the impact of a more than 20 log point decline in the number of firms per worker in the U.S. since the early 1980s (panel a) on national level labor market outcomes. There are several important caveats associated with this approach, including the facts that we treat the estimates as causal and that we disregard any aggregate equilibrium effects that the cross-division variation absorbs in the time fixed effects. With these caveats in mind, panel b suggests that increases in labor market concentration could have been an important factor behind the decline in EE mobility that we observed over the past 40 years. In particular, a falling number of employers per worker predicts a roughly 40 log point decline in EE mobility, relative to the 90 log point fall in the data. It

	(1)	(2)	(3)	(4)	(5)
	EE	Δw	Acceptance Probability	λ^e	λ^n
Firms per worker	1.822** (0.694)	0.008*** (0.00273)	-0.199* (0.110)	2.919** (1.108)	0.304* (0.171)
N	72	72	72	72	72

Table 1: OLS estimates of equation (18) using data from nine U.S. Census divisions and eight five-year time periods between 1979–2018. All variables are in logs and all specifications include division and period fixed effects. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

accounts for about two-thirds of the decline in wage growth due to EE mobility (panel c). Furthermore, increasing labor market concentration predicts a *higher* acceptance probability (panel d), so that the decline in EE mobility is driven by a lower job finding probability of the employed (panel e). Finally, increases in labor market concentration are only associated with a quantitatively small decline in the job finding probability of the non-employed (panel f). These predictions are both qualitatively and quantitatively in line with U.S. national trends over this period.

6 Conclusion

We estimate a large decline in EE mobility toward higher paying jobs since the 1980s in the U.S., using a prototypical job ladder model and publicly available micro data. This methodology allows us to measure EE mobility during a period of rapid changes in the U.S. labor market, but for which data limitations have prevented the construction of direct EE mobility measures. Moreover, our methodology overcomes issues associated with non-random attrition, and it isolates the component of EE mobility that is directed toward higher paying jobs. It can easily be extended to incorporate more data over time.

We use our methodology to establish three facts on long-run trends in U.S EE mobility. First, EE mobility toward higher paying jobs halved between 1979 and 2023. Second, this decline translated to a fall in wage growth associated with EE mobility by over one percentage point. Third, women, minorities, those with a high school diploma or less, and workers belonging to newer cohorts saw particularly large declines.

We find that the decline in EE mobility can be accounted for largely by a lower job finding probability of the employed, as opposed to a lower acceptance probability of an outside job offer. At face value, this casts doubt on the hypothesis that EE mobility is lower today because workers are better matched. Moreover, we document that the decline in the job finding probability of the employed was not mirrored by a similarly large fall in the job finding probability of the non-

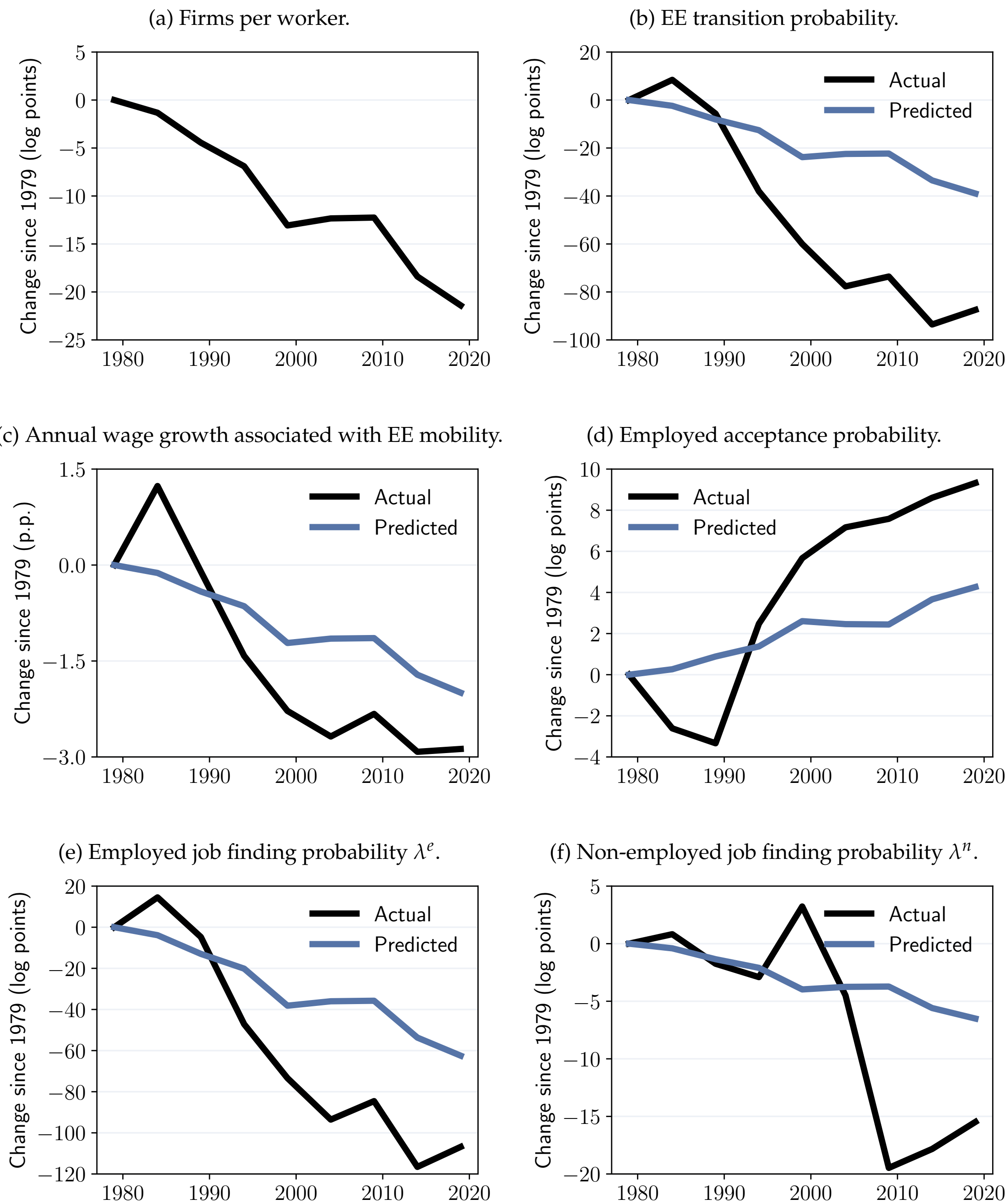


Figure 19: Panel (a) shows the change in market concentration as measured by firms per worker. The remaining panels show the actual (black) and predicted (blue) labor market variables where the prediction is the cross-sectional point estimate from regression (18) multiplied by the national change in concentration. Displayed in order are EE transition probability (b), the associated average wage change (c), the acceptance probability (d), the employed job-finding probability (e), and the non-employed job-finding probability (f). All variables are in logs.

employed, suggesting that the fall in EE mobility is not primarily the result of changes in matching efficiency or vacancy creation by firms. Instead, we argue that an increase in labor market concentration may have reduced workers' ability to find outside job opportunities, contributing to the disproportionate decline in EE mobility relative to NE mobility.

Future work should further investigate the causes of the decline of the U.S. job ladder and in particular its relationship with competition in the labor market, as well as whether policy can play a role in fostering a more dynamic, inclusive labor market.

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